



Analysis using Region Detection Techniques for fabric fault Identification

G.Lakshmi

Dept of Information Technology
P V P Siddhartha Institute of
Technology
Vijayawada, India.
lakshmineeraja@gmail.com

A.Haritha

Dept of Information Technology
P V P Siddhartha Institute of
Technology
Vijayawada, India.
akkinenih@gmail.com

Dr.PVS Lakshmi

Dept of Information Technology
P V P Siddhartha Institute of
Technology
Vijayawada, India.
papinenivsl@gmail.com

P.V. Naveen Kumar,
III/IV B.Tech,

P V P Siddhartha Institute of Technology
Vijayawada, India.

P. Geetanjali
III/IV B.Tech,

P V P Siddhartha Institute of Technology
Vijayawada, India.

Abstract: The fabric industry is the most revenue generating business in India. Production of the quality fabric is the ultimate goal of the business which requires producing less defective textile for minimizing production cost and time. Generally the assessment and inspection are done manually and it is more time consuming. An automotive and accurate inspection process is needed to reduce error on identifying fabric defects. If the faults are to be identified manually the time consumption is more comparatively less and the percentage of fault identification is deduced to a lower rate. The present work demonstrates that the method can detect the identifying fabric defects like hole, scratch, dirt spot, fly, crack point, colour bleeding. An analysis has been done on this by using different region detection techniques.

Keywords: Edge detection, canny, gaussain detector, harris laplace, Hessian detector.

I. INTRODUCTION

The fabric industry is the most revenue generating business in India. Production of the quality fabric is the ultimate goal of the business which requires producing less defective textile for minimizing production cost and time. Generally the assessment and inspection are done manually and it is more time consuming. The competition enhancement depends mainly on productivity and quality of the fabrics produced by each industry. In the textile sector, there have been an enlarge amount of losses due to faulty fabrics. A fault in a fabric can be hole, scratch, dirt spot, fly, crack point, colour bleeding. Also it has been observed that the price of textile fabric is reduced by 45% to 65% due to defects. Recognition of patterns independent of position, size, brightness and orientation in the visual field has been the goal of much recent work. Hence the efficiency is also reduced in this process. To overcome all these drawbacks we are applying point of interest along with the edge detection techniques to identify the faults like scratch, crack point, hole. This could enhance the faulty fabric identification rates. An analysis is done by observing the results obtained on applying the region detection techniques.

Proposed Methodology

The sequence of steps to be followed in this methodology
Step 1: Colour fabric image given as input
Step 2: Conversion of the colour image to gray level image
Step 3: Filtering by noise removal technique.
Step 4: Conversion of noise removal image to binary image
Step 5: Apply Canny Edge detection technique.
Step 6: Apply point of interest
Step 7: Observing the results using various region detection

techniques

1.1. Colour fabric image given as input

The fabric image is given as input and the following procedure is applied to the image.

1.2. Conversion of the colour image to gray level image

The most common techniques are based on weighted means of the red, green, and blue image channels (e.g., *Intensity* and *Luminance*), but some methods adopt alternative strategies to generate a more perceptually accurate representation (e.g., *Luma* and *Lightness*) or to preserve subjectively appealing color contrast information in grayscale images (e.g., *Decolorize*).

If each color pixel is described by a triple (R, G, B) of intensities for red, green, and blue. to convert the color image to grey level image. We use The **lightness** method averages the most prominent and least prominent colors.

1.3 Filtering by noise removal technique.

Random Variation Impulsive Noise (RVIN) This type of noise is also called the Gaussian noise or normal noise is randomly occurs as white intensity values. Gaussian distribution noise can be expressed by: $P(x) = 1/(\sigma\sqrt{2\pi}) * e^{-(x-\mu)^2 / 2\sigma^2}$ $-\infty < x < \infty$. An image may be "dirty" (with dots, speckles, stains) To remove speckles/dots on an image Dots can be modeled as impulses (salt-and-pepper or speckle) or continuously varying (Gaussian noise) – Can be removed by taking mean or median values of neighboring pixels.

Gaussian Filter: A Gaussian filter smoothes an image by calculating weighted averages in a filter box.

$$g(i, j) = c \cdot e^{-\frac{i^2 + j^2}{2\sigma^2}}$$

Filtering with a $m \times m$ mask – the weights are computed according to a Gaussian function: – σ is user defined

1.3 Conversion of noise removal image to binary image

A binary image is a digital image that has only two possible values for each pixel. Typically the two colors used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. In the document-scanning industry this is often referred to as "bi-tonal".

Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit—i.e., a 0 or 1. The names black-and-white, B&W, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as grayscale images. In Photoshop parlance, a binary image is the same as an image in "Bitmap" mode.

Binary images often arise in digital image processing as masks or as the result of certain operations such as segmentation, thresholding, and dithering. Some input/output devices, such as laser printers, fax machines, and bilevel computer displays, can only handle bilevel images.

A binary image can be stored in memory as a bitmap, a packed array of bits. A 640×480 image requires 37.5 KiB of storage. Because of the small size of the image files, fax machine and document management solutions usually use this format. Most binary images also compress well with simple run-length compression schemes.

Binary images can be interpreted as subsets of the two-dimensional integer lattice Z^2 ; the field of morphological image processing was largely inspired by this view.

An entire class of operations on binary images operates on a 3×3 window of the image. This contains nine pixels, so 512 possible values. Considering only the central pixel, it is possible to define whether it remains set or unset, based on the surrounding pixels. Examples of such operations. are thinning, dilating, finding branch points and endpoints, removing isolated pixels, shifting the image a pixel in any direction, and breaking H-connections. Conway's Game of Life is also an example of a 3×3 window operation.

1.4 Apply Canny Edge detection technique

Primary edge detection steps:

1. Smoothing: suppress noise
2. Edge enhancement: filter for contrast
3. Edge localization

Determine which local maxima from filter output are actually edges versus. noise

Steps in Edge Detection

Edge detection contain three steps namely Filtering, Enhancement and Detection. The overview of the steps in edge detection are as follows.

1) Filtering: Images are often corrupted by random variations in intensity values, called noise. Some common types of noise are salt and pepper noise, impulse noise and Gaussian noise. Salt and pepper noise contains random occurrences of both black and white intensity values. However, there is a trade-off between edge strength and noise reduction. More filtering to reduce noise results in a loss of edge strength.

2) Enhancement: In order to facilitate the detection of edges, it is essential to determine changes in intensity in the neighborhood of a point. Enhancement emphasizes pixels where there is a significant change in local intensity values and is usually performed by computing the gradient magnitude.

3) Detection: Many points in an image have a nonzero value for the gradient, and not all of these points are edges for a particular application. Therefore, some method should be used to determine which points are edge points. Frequently, thresholding provides the criterion used for detection.

II. CANNY EDGE DETECTION

Canny edge detector is one of the most commonly used image processing tools. It detects edges in a very robust manner. Unlike Roberts Cross and Sobel, the canny operation is not very susceptible to noise. It takes less time than Roberts cross. It is one of the most important methods to find the edges by separating noise from input image. The algorithm is adaptable to various environments. It is a better method because it extracts the features in an image without disturbing its features. There are certain criteria to improve current methods of edge detection. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed. The second criterion is that the edge points be well localized i.e. the distance between the edge pixels as found by the detector and the actual edge should be minimum. A third criterion is to have only one response to a single edge.

2.1 Importance of Canny:

Despite of number of edge detection techniques available canny algorithm is considered because it contains a number of adjustable parameters which can affect the computation time and effectiveness of the algorithm.

a) The size of the Gaussian filter: The smoothing filter used in the first stage directly affects the results of the detection of small, sharp lines. A larger filter causes more blurring, smearing out the value of an given pixel over a larger area of image.

b) The use of two thresholds with hysteresis allows more flexibility than in a single-threshold. A threshold set too high can miss important information. On the other hand, a threshold set too low will falsely identify irrelevant information (such as noise) as important. The edge detection in this technique is optimized with regard to the following criteria.

i) Maximizing the signal-to-noise ratio of the gradient.

- ii) Edge localization for ensuring the accuracy of edge.
- iii) Minimizing multiple responses to a single edge.

III. APPLY POINT OF INTEREST

Interest point detection is a recent terminology in computer vision that refers to the detection of interest points for subsequent processing. An interest point is a point in the image which in general can be characterized as follows:

- it has a clear, preferably mathematically well-founded, definition,

- it has a well-defined position in image space

- the local image structure around the interest point is rich in terms of local information contents (e.g.: significant 2D texture)], such that the use of interest points simplify further processing in the vision system,

- it is stable under local and global perturbations in the image domain as illumination/brightness variations, such that the interest points can be reliably computed with high degree of reproducibility.

Optionally, the notion of interest point should include an attribute of scale, to make it possible to compute interest points from real-life images as well as under scale changes.

Types of Images:

Edges

Edges are points where there is a boundary (or an edge) between two image regions. In general, an edge can be of almost arbitrary shape, and may include junctions. In practice, edges are usually defined as sets of points in the image which have a strong gradient magnitude. Furthermore, some common algorithms will then chain high gradient points together to form a more complete description of an edge. These algorithms usually place some constraints on the properties of an edge, such as shape, smoothness, and gradient value. Locally, edges have a one-dimensional structure.

Corners / interest points

The terms corners and interest points are used somewhat interchangeably and refer to point-like features in an image, which have a local two dimensional structure. The name "Corner" arose since early algorithms first performed edge detection, and then analysed the edges to find rapid changes in direction (corners). These algorithms were then developed so that explicit edge detection was no longer required, for instance by looking for high levels of curvature in the image gradient. It was then noticed that the so-called corners were also being detected on parts of the image which were not corners in the traditional sense (for instance a small bright spot on a dark background may be detected). These points are frequently known as interest points, but the term "corner" is used by tradition.

Blobs / regions of interest or interest points

Blobs provide a complementary description of image structures in terms of regions, as opposed to corners that are more point-like. Nevertheless, blob descriptors may often contain a preferred point (a local maximum of an operator response or a center of gravity) which means that many blob

detectors may also be regarded as interest point operators. Blob detectors can detect areas in an image which are too smooth to be detected by a corner detector.

Consider shrinking an image and then performing corner detection. The detector will respond to points which are sharp in the shrunk image, but may be smooth in the original image. It is at this point that the difference between a corner detector and a blob detector becomes somewhat vague. To a large extent, this distinction can be remedied by including an appropriate notion of scale. Nevertheless, due to their response properties to different types of image structures at different scales, the LoG and DoH blob detectors are also mentioned in the article on corner detection.

$$w(x, y) = g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$H(\mathbf{x}) = \begin{bmatrix} L_{xx}(\mathbf{x}) & L_{xy}(\mathbf{x}) \\ L_{xy}(\mathbf{x}) & L_{yy}(\mathbf{x}) \end{bmatrix}$$

Ridges

For elongated objects, the notion of ridges is a natural tool. A ridge descriptor computed from a grey-level image can be seen as a generalization of a medial axis. From a practical viewpoint, a ridge can be thought of as a one-dimensional curve that represents an axis of symmetry, and in addition has an attribute of local ridge width associated with each ridge point. Unfortunately, however, it is algorithmically harder to extract ridge features from general classes of grey-level images than edge-, corner- or blob features. Nevertheless, ridge descriptors are frequently used for road extraction in aerial images and for extracting blood vessels in medical images.

IV. FEATURE EXTRACTION

Once features have been detected, a local image patch around the feature can be extracted. This extraction may involve quite considerable amounts of image processing. The result is known as a feature descriptor or feature vector. Among the approaches that are used to feature description, one can mention N-jets and local histograms (see scale-invariant feature transform for one example of a local histogram descriptor). In addition to such attribute information, the feature detection step by itself may also provide complementary attributes, such as the edge orientation and gradient magnitude in edge detection and the polarity and the strength of the blob in blob detection.

An observation has been noted by applying region detection techniques.

- Gaussian Detector
- Harris Laplace Detector
- Hessian detector

Harris Laplace Detector: In order to determine salient points, Harris-Laplace relies on a Harris corner detector. By applying it on multiple scales, it is possible to select the characteristic scale of a local corner using the Laplacian operator. The Harris detector uses the second moment matrix as the basis of its corner decisions. The matrix A, has also been called the autocorrelation matrix and has values closely related to the derivatives of image intensity.

where I_x and I_y are the respective derivatives (of pixel intensity) in the x and y direction at point X and p and q are the values of the weighting function. The off-diagonal entries are the product of I_x and I_y while the diagonal entries are squares of the respective derivatives. The weighting function can be uniform, but is more typically an isotropic, circular Gaussian, that acts to average in a local region while weighting those values near the center more heavily.

Hessian Affine Detector: it calculates the corner strength as the determinant of the Hessian matrix. The local maxima of the corner strength denote the corners in the image. The determinant is related to the Gaussian curvature of the signal and this measure is invariant to rotation.

The Harris affine detector relies on interest points detected at multiple scales using the Harris corner measure on the second-moment matrix. The Hessian affine also uses a multiple scale iterative algorithm to spatially localize and select scale & affine invariant points. However, at each individual scale, the Hessian affine detector chooses interest points based on the Hessian matrix at that point: where $L_{aa}(\mathbf{x})$ is second partial derivative in the \mathbf{a} direction and $L_{ab}(\mathbf{x})$ is the mixed partial second derivative in the \mathbf{a} and \mathbf{b} directions. It's important to note that the derivatives are computed in the current iteration scale and thus are derivatives of an image smoothed by a Gaussian kernel:

$$L(\mathbf{x}) = g(\sigma_I) \otimes I(\mathbf{x})$$

As discussed in the Harris affine region detector article, the derivatives must be scaled appropriately by a factor related to the Gaussian kernel: σ_I^2 .

At each scale, interest points are those points that simultaneously are local extrema of both the determinant and trace of the Hessian matrix. The trace of Hessian matrix is identical to the Laplacian of Gaussians (LoG):

V. RESULTS AND DISCUSSIONS

[1] The Colour fabric image is given as input



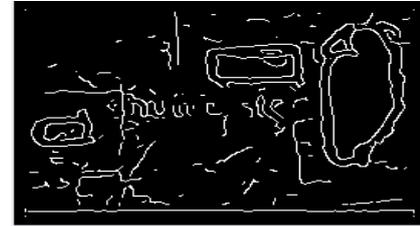
[2] This Colour fabric image is converted to grey scale



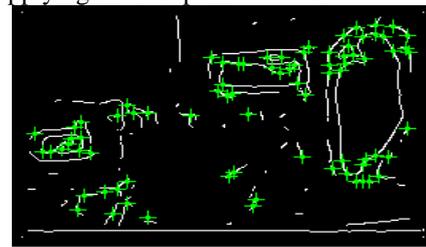
[3] The result after applying Noise Removal



[4] On applying Canny Edge detection technique



[5] On applying Interest point detector



VI. OBSERVATIONS

The original Image:



[1] On applying Gaussian Detector:



point of interest on applying Gaussian Detector

| PointsOfInterestSet | | | | | | | |
|---------------------|-----|-------|--------|-------|------|-------------|--|
| X | Y | Width | Height | Sigma | Type | Orientation | |
| 24 | 99 | 0 | 0 | ? | SIFT | 1.293 | |
| 192 | 41 | 0 | 0 | ? | SIFT | -0.155 | |
| 130 | 45 | 0 | 0 | ? | SIFT | 1.285 | |
| 59 | 100 | 0 | 0 | ? | SIFT | 2.955 | |
| 137 | 68 | 0 | 0 | ? | SIFT | -1.825 | |
| 55 | 157 | 0 | 0 | ? | SIFT | 0.340 | |
| 244 | 97 | 0 | 0 | ? | SIFT | 0.433 | |
| 87 | 173 | 0 | 0 | ? | SIFT | -1.703 | |
| 203 | 114 | 0 | 0 | ? | SIFT | 2.815 | |
| 192 | 116 | 0 | 0 | ? | SIFT | -0.178 | |
| 164 | 42 | 0 | 0 | ? | SIFT | 1.531 | |
| 86 | 91 | 0 | 0 | ? | SIFT | -2.933 | |
| 205 | 47 | 0 | 0 | ? | SIFT | 2.808 | |
| 23 | 110 | 0 | 0 | ? | SIFT | 0.808 | |
| 140 | 55 | 0 | 0 | ? | SIFT | 1.579 | |
| 83 | 103 | 0 | 0 | ? | SIFT | -2.055 | |
| 34 | 75 | 0 | 0 | ? | SIFT | 2.959 | |
| 102 | 90 | 0 | 0 | ? | SIFT | -0.649 | |

| X | Y | Width | Height | Sigma | Type | Orientation |
|-----|-----|-------|--------|-------|------|-------------|
| 136 | 67 | 0 | 0 | ? | SURF | 0 |
| 223 | 134 | 0 | 0 | ? | SURF | 0 |
| 22 | 79 | 0 | 0 | ? | SURF | 0 |
| 253 | 22 | 0 | 0 | ? | SURF | 0 |
| 244 | 25 | 0 | 0 | ? | SURF | 0 |
| 47 | 156 | 0 | 0 | ? | SURF | 0 |
| 64 | 106 | 0 | 0 | ? | SURF | 0 |
| 198 | 81 | 0 | 0 | ? | SURF | 0 |
| 134 | 126 | 0 | 0 | ? | SURF | 0 |
| 200 | 24 | 0 | 0 | ? | SURF | 0 |
| 164 | 65 | 0 | 0 | ? | SURF | 0 |
| 128 | 61 | 0 | 0 | ? | SURF | 0 |
| 214 | 125 | 0 | 0 | ? | SURF | 0 |
| 163 | 94 | 0 | 0 | ? | SURF | 0 |
| 64 | 124 | 0 | 0 | ? | SURF | 0 |
| 39 | 151 | 0 | 0 | ? | SURF | 0 |
| 100 | 83 | 0 | 0 | ? | SURF | 0 |
| 86 | 34 | 0 | 0 | ? | SURF | 0 |
| 152 | 156 | 0 | 0 | ? | SURF | 0 |

VII. CONCLUSION

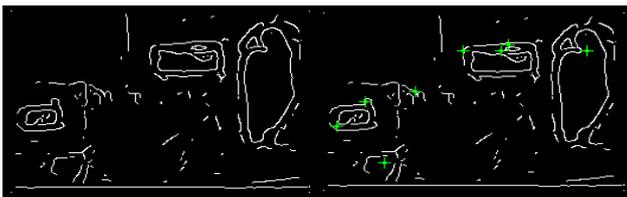
The methodology proposed is capable of detecting fabrics’ defects with more accuracy and efficiency. In the research arena, our process uses Edge detection techniques to find out the hole, scratch point ,crack point and point of interest has been applied to identify the variations of area of faulty portion like color bleeding. As an extension to this we have applied the three region detection techniques like gaussian detection technique, Harris Laplace, Hessian detector techniques.

As a result, a variation of performance is noticed, in identifying other faults than hole and scratch faults .The combination of the techniques applied on the fabric resulted in a more perfect material which can be consumed by the Textile industry.

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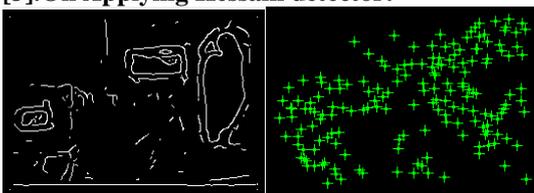
[2]On Applying Harris Laplace:



Point of interest Result on applying Harris Laplace

| PointsOfInterestSet | | | | | | | |
|---------------------|-----|-------|--------|-------|---------|-------------|--|
| X | Y | Width | Height | Sigma | Type | Orientation | |
| 58 | 154 | 0 | 0 | 30 | Ellipse | ? | |
| 228 | 44 | 0 | 0 | 75 | Ellipse | ? | |
| 156 | 44 | 0 | 0 | 119 | Ellipse | ? | |
| 42 | 94 | 0 | 0 | 30 | Ellipse | ? | |
| 162 | 38 | 0 | 0 | 30 | Ellipse | ? | |
| 18 | 118 | 0 | 0 | 30 | Ellipse | ? | |
| 124 | 44 | 0 | 0 | 87 | Ellipse | ? | |
| 84 | 84 | 0 | 0 | 75 | Ellipse | ? | |

[3].On Applying Hessain detector:



Point of interest result on applying Hessain detector